Detection of Defects in Solar Panels Using Image Processing

Project Report

Submitted in partial fulfillment of requirement for the award in the degree of

Bachelor of Engineering

in

Electronics and Communication Engineering

by

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June 2020

DECLARATION CERTIFICATE

This is to certify that the work presented in this project entitled " **Detection of Defects in Solar Panels using Image Processing**", in partial fulfilment of the requirement for the award of Degree of **Bachelor of Engineering in Electronics & Communication Engineering**, submitted to the Department of Electronics & Communication Engineering of Birla Institute of Technology, Mesra, Ranchi, Jharkhand is a bona fide work carried out by **Likhitha Potluri ,Renuka Chintalapati** and **Karuturi Satya Sai Teja** under my supervision and guidance.

To the best of my knowledge, the content of this project, either partially or fully, has not been submitted to any other institution for the award of any other degree.

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CERTIFICATE OF APPROVAL

This is to certify that the project entitled "**Detection of Defects in Solar Panels using Image Processing**" is hereby approved as a suitable design of an engineering subject, carried out and presented in satisfactory manner to warrant its acceptance as prerequisite to the degree for which it has been submitted.

It is understood that by this approval, the undersigned do not necessarily endorse any conclusion drawn or opinion expressed therein, but approve the project for which it is submitted.

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ACKNOWLEDGEMENT

We owe our deepest gratitude to our advisor **Dr. Prajna Parimitha Dash**, for her constant support and motivation, despite her extremely busy schedule. Our interactions with her always resulted in new ideas and proved beneficial towards our work. Without her constant presence and supervision our work would not have been successful.

We are very grateful to **Dr. S. Pal, Professor and Head, Department of Electronics and Communication Engineering, Birla Institute of Technology, Mesra** for extending all the facilities at all times for pursing this course.

And lastly our batch mates who have always been there with valuable suggestions and support in our endeavours.

Likhitha Potluri

Renuka Chintalapati

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ABSTRACT

Solar cell panels are the devices which convert solar energy into electrical energy. Manufacturing does not often produce perfect solar cells. These modules can be subjected to various internal and external stresses. These factors can create many no. of defects in the panel. Proper monitoring and maintenance are thus important to assure solar cell lifetime and its appropriate energy performance. Its function can only be enhanced by properly detecting the defects in it. This project proposes an applicable approach of digital image processing technique in solar cell inspection. Solar cell defects can be detected by different methods including thermal imaging, electroluminescence and image enhancement techniques and segmentation process. Hotspots, microcracks etc are the main defects found in the cell.

After the defects have been found out using the above techniques, the defects are now classified into various types by two algorithms. These are written in the python language. The algorithm for solar cell defect detection by digital image processing using support vector machine and convolutional neural networks has been written and the respective accuracies found out.

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INTRODUCTION

In the 21-st century the technologies allowed people to think about alternative energy resources, which are clear and natural. One of such kind of energy resources is solar energy, which could be gathered by using solar cells. The solar cells initially were expensive, but nowadays they are becoming cheaper and can be used instead of traditional energy resources in many countries. These are renewable resources of energy and are the devices which convert solar energy into electrical energy. The main challenge in this area is the quality of solar cells and its robustness. So, it is important to perform an initial inspection for detecting the defects on solar cells.

When a large no. of solar panels are placed in a solar plant, it may be subject to many different failures and defects (e.g. snail trails, hot spot, micro cracks, cell breakage, delamination, bubbles, yellowing, discoloration, oxidation, corrosion, etc.) due to the weather condition such as wind, sand, humidity, high UV radiation and other internal and external stresses. It is physically not feasible for humans to detect the defective panels.

However, most of these stresses cause power losses in the solar cells, hence investigate about inspection methods of solar cell panels is a significant issue in solar energy field. Thus, the lifetime of solar cell primarily depends on monitoring and maintenance and early defects detection can hamper to deploy of the degradation part on PV modules.

Solar cells can have various defects like damages, shading and bad interconnections. Shunts and cracks in solar cells appear as hot spots. Thermal imaging is the technique of using the heat given off by an object to produce an image of it or to locate it. This technique converts small temperature differences existing in natural scenes to a visual picture with no source of illumination required. Hence it can work effectively during day or night. The thermal images are procured and the detect defection has been done.

The detection of defects has been done by various image enhancement techniques and segmentation process was also used. Electroluminescence (EL) imaging is a non-destructive technology for failure analysis of PV modules with the ability to image solar modules at a much higher resolution. Since disconnected parts do not irradiate, it is not possible to capture and detect defects using infrared or thermal imaging. EL imaging has an advantage over that.

CHAPTER 1

Introduction to Solar Panels and Image Processing

1.1 Importance of Solar Energy and Solar Panels:

Solar energy is an abundant power resource to solve energy needs with less impact on environment. Unlike solar, conventional sources such as coal, oil are non – renewable sources. Everyday sun gives far more energy than required to power everything. Hence utilisation of this power is very important and also heavy investments are done for implementation of solar plants. Some of the advantages which make solar plants important now- a-days are

1.***Renewable source***: Fossil fuels like coal may run out anytime soon but solar power is limitless. It is a free source of energy, unlimited and inexhaustible. The only limitation is our ability to turn into electricity in an efficient and cost-effective way

2.***Solar energy – A clean source:*** When we use solar energy to convert into electricity, no greenhouse gases like carbon-dioxide or ozone are released into atmosphere. It is safe and environment -friendly and it does not release any chemicals that pollute the atmosphere.

3.***Low operating costs*** : Operational costs are very low compared to other forms of power generation because no fuel is required to run the solar plant. Hence solar energy can create large amounts of electricity without the expense of saving a fuel supply.

4.***Can use underutilised land*** : There are many barren lands which are not used either for agriculture or development purposes. Hence we can use those lands for installing solar panels and utilize them efficiently.

5.***Less electricity loses:*** Electricity generally needs to be transported via long distance transmission lines which results in power losses. By installing solar panels on roof tops ,there is no need for long distance transmission and one can be in control of their own electricity bills. There will be less risk regarding electricity bill spikes. It can save up to 20% of energy costs and easy to install .no more extra place required because it can be installed on places like roof tops. It requires less manpower compared to other power generation process.

Hence solar energy can be used for heating purposes, business purpose, lighting homes and streets and a variety of commercial ,industrial and residential purposes

Fig 1.1: A group of Solar Panels by Tata Power Group

1.2 Working Principle of Solar Cell:

The working principle of solar cell is based on a effect called PHOTOVOLTAIC EFFECT. It is the generation of a potential difference at the junction of two different materials in response to electromagnetic radiation. It is closely related to the photoelectric effect, where electrons are emitted from a material that has absorbed light with a frequency above a material-dependent threshold frequency.

The photovoltaic effect can be divided into three basic processes:

1. Generation of charge carriers due to the absorption of photons in the materials that form a junction: Absorption of a photon in a material means that its energy is used to excite an electron from an initial energy level E_i to a higher energy level E_f. If an electron is excited from E_i to E_f, a void is created at E_i. This void behaves like a particle with a positive elementary charge and is called a hole. The absorption of a photon therefore leads to the creation of an electron-hole pair.. The radiative energy of the photon is converted to the chemical energy of the electron-hole pair.
2. Subsequent separation of the photo-generated charge carriers in the junction: A solar cell has to be designed such that the electrons and holes can reach n-type and p-type materials before they recombine, i.e. the time it requires the charge carriers to reach the membranes(n-type and p-type) must be shorter than their lifetime.
3. Collection of the photo-generated charge carriers at the terminals of the junction: Finally, the charge carriers are extracted from the solar cells with electrical contacts so that they can perform work in an external circuit. The chemical energy of the electron-hole pairs is finally converted to electric energy.

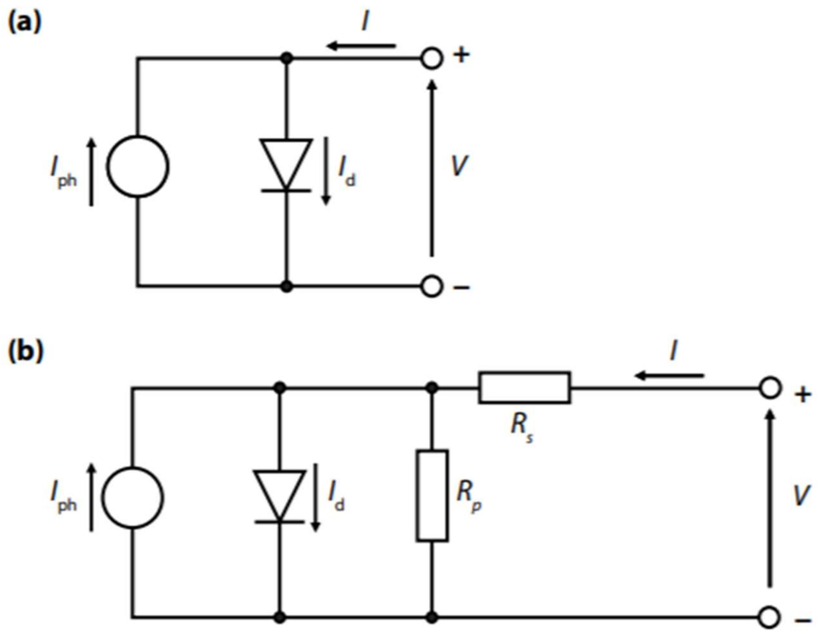


Fig 1.2 : (a) The equivalent circuit of (a) an ideal solar cell and (b) a solar cell with series resistance Rs and shunt resistance Rp.

1.3 Efficiency of a Solar Cell:

The main parameters that are used to characterise the performance of solar cells are

1. The peak power(Pmax)

2. The short-circuit current density (Jsc):The Jsc depends on the area of the solar cell. In order to remove the dependence of the solar cell area on Isc, often the short-circuit current density is used to describe the maximum current delivered by a solar cell.

3. The open-circuit voltage(Voc):The open-circuit voltage is the voltage at which no current flows through the external circuit. It is the maximum voltage that a solar cell can deliver.

4. The fill factor (FF):The fill factor is the ratio between the maximum power(Pmax = JmppVmpp) generated by a solar cell and the product of Voc with Jsc.

FF =Pmax/JscVoc

The subscript "mpp" in denotes the maximum power point (MPP) of the solar cell at which the solar cell has the maximal power output.

Conversion efficiency:

The conversion efficiency is calculated as the ratio between the maximal generated power and the incident power. The irradiance value Pin of 1000 W/m2 for the AM1.5 spectrum has become a standard for measuring the conversion efficiency of solar cells,

η = Pmax/Pin= JmppVmpp/Pin=Jsc Voc FF/Pin

Typical external parameters of a crystalline silicon solarcell are; Jsc ≈ 35 mA/cm2, Voc up to 0.65 Vand FF in the range 0.75 to 0.80. The conversion efficiency lies in the range of 17 to 18%.

Efficiency of a solar panel:

The efficiency of a solar panel is given by

η=(Pmax / E*Ac) *100; where

Pmax = Maximum power output(in W)

E = incident radiation flux(in W/m^2)

Ac = area of collector(in m^2)

1.4 Difficulties in Monitoring:

Solar plants are typically set up at remote locations, making them difficult to monitor continuously, by providing an experienced team of site engineers. The solar plants also involve a diverse set of devices like inverters, solar panel strings, transformers, weather stations, energy meters, etc. The overall energy generation and the performance of plant depend upon how well this diverse setup is maintained overtime. The other factors like dust, bird droppings, smoke, dew, soil, cable cuts, failure of inverters, hot-spots in panels these factors degrade the performance of energy generation and reduce the production almost by 20%.Additionally, the energy production is not only dependent on the performance of the equipment, but also on external factors like solar irradiation and ambient temperature, etc. Thus, in order to evaluate the performance of the plant and identify inefficiencies in a timely manner, it requires an intelligent real-time monitoring and maintenance system that is capable of incorporating external context information (such as weather condition, dust level, etc.)and identifying the device malfunctioning, thereby reducing the plant downtime.

1.5 Motivation:

Identification of fault, its detection, protection and fault analysis are necessary to prevent unexpected events in solar photovoltaic (PV) systems. In spite of the fact that Solar PV systems have no moving parts and generally require low maintenance, they still have more number of chances to get various failures or faults along the PV arrays, PV modules, batteries, wiring, and power conditioning units and interconnections to utility. It is difficult to shut down PV modules completely during faults, since they are energized by sunlight in daytime. Also, PV is modular technology in which PV power plant can be made by connecting a large number of PV modules in series and parallel configuration. Once PV modules are electrically connected, any fault among them can affect the entire system performance. In a large PV solar module, it may be very difficult to properly identify or detect a fault. It can remain hidden in the PV system or unidentified until the whole system collapse or breaks down. In addition, the series and parallel combinations of solar PV arrays or solar PV modules for increasing the voltage and current capability also increases the magnitude of high short circuit current leading to various faults.

Fire hazards not only show the weakness in conventional fault detection and protection schemes in PV arrays, but also reveal the urgent need of a better way to prevent such issues.

1.6 Objectives:

Identification of defects using image processing techniques

To use different image processing techniques like segmentation, histogram equalisation and Fourier transform techniques on an affected PV module to identify the defects

Study of thermal imaging

To study thermal imaging which is the most common technique to detect defects and failures on the PV modules and to study advantages and disadvantages of thermal imaging

Study of EL imaging

To study the importance of electroluminescence imaging in detecting the defects and to learn its advantages and disadvantages

Classification using support vector machine (SVM) and convolution neural network (CNN)

To use CNN and SVM classifiers to classify the dataset into functional and defective solar panels. To find out the efficiency of both classifiers and comparing to find out the best approach.

1.7 Various Defects in Solar Panels:

The solar panels are installed in an open atmosphere and subjected to the environment directly. This direct contact of solar panels towards the environment develop certain defects in solar photo-voltaic panels.

Environmental Factors :

Components of solar panel	Defects in solar panel	Possible reasons	Effect of defects
Frame	Corrosion of frame and interconnect, deframing	Subject to open atmospheric effects(moisture, dust, detachment of sealing and adhesive between frame and panel parts.	Risk electric shock, reduced expected life
Glass surface	Cracking of transparent glass, soil deposition on panel glass surface	Mishandling, lack in maintenance, dusty and soily environment	Degradation of ARC (discoloration, delamination), corrosion of cells, possibility of electric shock, reduced power generation
EVA encapsulant	Yellowing	Degradation of adhesive material between glass and cell due to high temperature, UV and water exposure	Change in transmittance of light falling on solar cell cause reduction in power generation
Solar cells and bus bars	Discoloration (blue from purple), burn marks in bus bars	Poor EVA quality, high temperature, oxidation of ARC, heating of module parts to show burn mark	Reduction in energy generation due to less absorption of solar irradiance by discolored cell, discolor encapsulant by burn marks
Backsheet of solar module surface	Bubbles, rupture, chalking of back sheet	Release heat dissipation of cells from back surface at high temp., transportation or heating due to temp., due to thermal degradation and poor quality material of back sheet	Reduce life of cell, formation of hotspots, reduce performance of heated portion, less reduction in generated power, moister and risk of electrical shock
Junction box	Corrosion	Moisture due to loose sealing contact	Reduce life of junction box components
Table terms: ARC (Anti-reflective coating), EVA (Ethylene vinyl acetate)			

Table 1.1 : Visually identified environmental defects in solar panels

Shading of tree, bird deposits, cement deposits, soiling, e high buildings, lightning rods, masts (pylons) or trees next to the PV power plant are some of the environmental factors which cause reduction in power generation from solar panels in heat form.

Effect of shading of tree:

When shade of tree falls on solar panels, the solar cells under shade attain less solar irradiance as compared to unshaded solar cells therefore unshaded solar cells act as a load and draw power instead of supplying. This causes formation of hotspots on shaded areas of solar panel surface and release heat. The temperature of hotspot area becomes more which may damage the solar cell. The second important issue is regarding loss of power which is wasted during shading of solar cell. A lot of generated power is radiated in heat form when hotspots are formed during shading effect.

Micro Cracks:

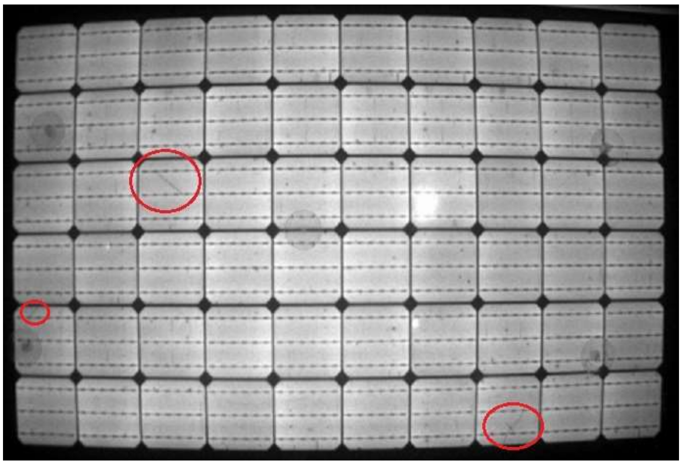


Fig 1.3 : EL image showing microcracks

Micro cracks occurs in solar cell is a normal problem and cannot be avoided. As the name is micro means the output power is affected by a very small crack occurs in the PV panel. The crack may occur due the following reasons:

1. Due to the mechanical stress and the shocks occurs during the transportation.

2. Due to the aging factor.

3. Due to the increase in the temperature

Snail Tracks:

Snail tracks are a product of the formation of silver carbonate (AgZC03) Nano-particles which discolour the silver grid. These are usually some discoloured lines both on mono and multi crystalline silicon solar modules due to a local discoloration of the Ag contact fingers. So far known, snail tracks occur on the cell edges or close to the Micro Cracks in the Solar PV. These tracks are dependent on material and process induced sources Hotspot .This is occurs due to the overheating for a defect known as shunts. This fault takes place along with the normal degradation of material of the solar PV module. During Hotspot, the defected area shows an increased temperature with respect to the remaining cells .

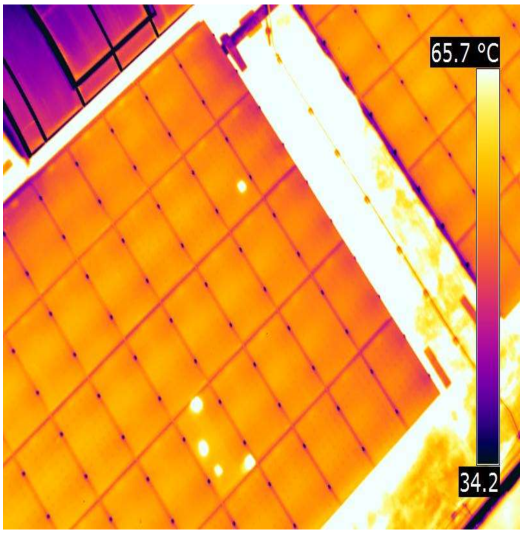


Fig 1.4 : Thermal Image Showing Hotspots

The reasons for the appearance of hot spots are multiple and can be classified into **functional or operational**.

Functional reasons can be divided into two areas:

- **Cell mismatch,** which occurs when cells of different current are connected in series.

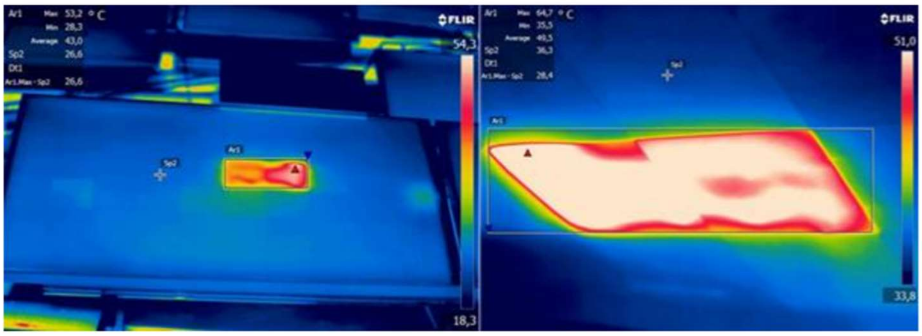


Fig 1.5: A overheated cell due to internal cell problems

- **Damage or poor quality of the solar cell**, which can occur during manufacture, due to the fact that the silicon cell will be subjected to a stressful process during rolling, handling and transportation.

The operational reasons for the hot spots are related to the design and operation of the photovoltaic installation, and may include:

- **Seasonal shadows on solar panels:**

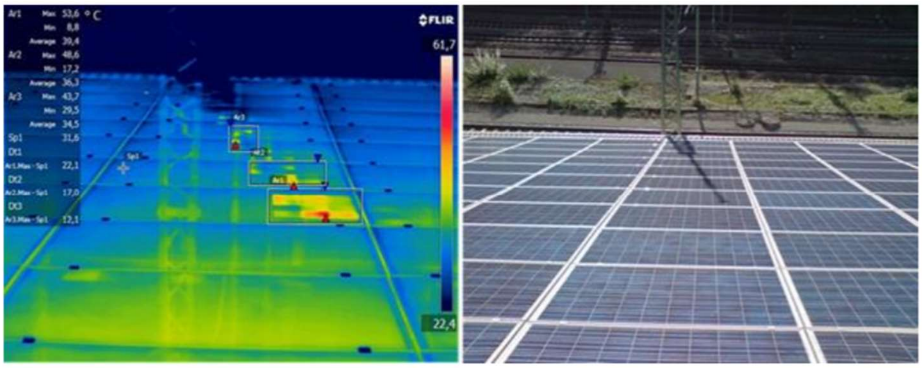


Fig 1.6 : Overheated cells due to shading by metal rod

An installer company may accept shading conditions in winter to increase electricity production in summer. But as a result, the panels will suffer systematic shading of the lower row of cells every morning and night during the winter. If it is necessary to do so, then a possible solution would be to install the panels in a horizontal orientation, which would allow the bypass diodes to be driven at critical times and allow the generation of electricity while minimizing damage by hot spots, even in winter. In addition to connecting the shaded series to different inverter inputs.

- **Roof conditions:** Roofs may have areas where shadows are cast. When the cells of a photovoltaic panel are completely shaded (by system design), this can mean that bypass diodes are not used, resulting in an increase in temperature that will degrade the panel.
- **Partial shading** due to trees or vegetation.

Fig 1.7: PV module shows overheated cells due to shading by plants

- **Dirt and sand:**

Photovoltaic panels can become dirty from dust, suspended sand, dirt and other contaminating impurities during their service life. Your maintenance company should identify situations that require cleaning by making periodic visits to the facility. The frequency of cleaning will depend largely on the weather, the conditions and terrain surrounding the park, as well as whether or not the solar panels have drainage corners.

Fig 1.8 : Overheated cells due to shading by medium voltage lines

Packaging material faults :

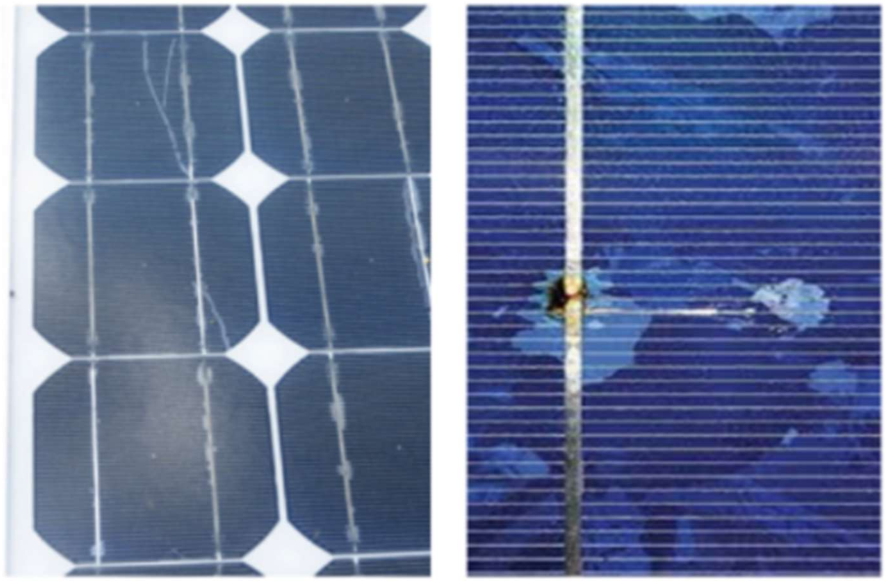
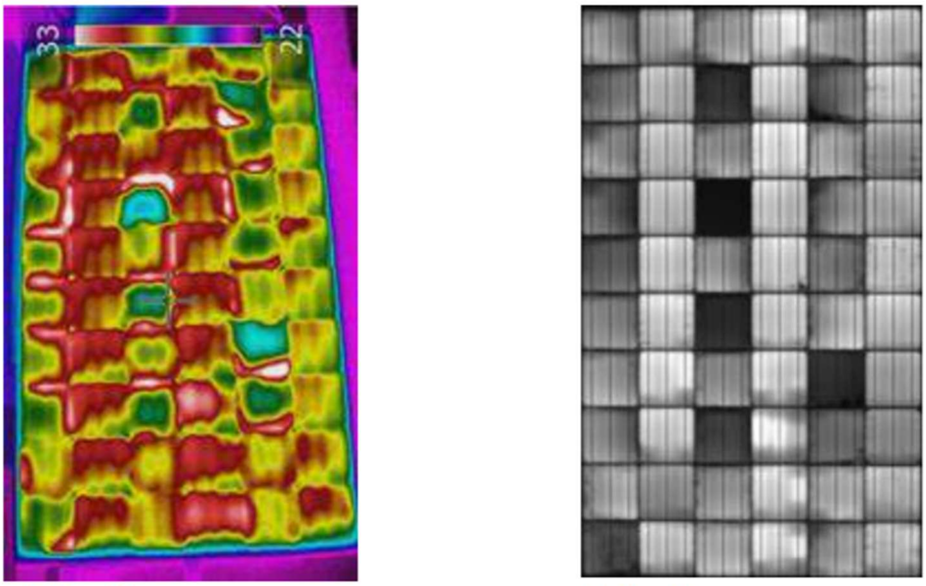


Fig 1.9: Figure showing defects due to packaging faults

Module package degradation is a major problem, which results in poor module performance and a safety hazard. Even though, it is often overlooked because package degradation is very slow and hard to detect. The package material faults occur due to the aging of the module, hot spot, moisture occurs in the system. Package damage can produce safety hazards in high voltage systems due to the lack of protective insulation. Such failures may induce electric shock and create a pathway for electrochemical corrosion. The potential shock hazard can be worsened by moisture intrusion into the package. Some typical module package degradations include glass breakage, encapsulate discoloration and delaminating.

Potential Induced Degradation (PID) :



a) IRT at I_{sc} b) EL at I_{sc}

Fig 1.10: IR thermography and EL image of a PID-s affected module at the same applied test current (Itest = Isc) in the dark. a) The IRT image shows that the strongly affected cells are cooler than the rest. b) The EL image shows that the affected cells are darker .

PID is one of the defects that has gained the attention of PV experts in recent years. This problem can arise when a voltage difference occurs between the panel and the earthing. In order to increase the voltage of the PV generators, the modules are connected in series to form PV strings. The voltages of the strings can reach up 1500 V in grid-connected plants. The frames of the modules are mechanically connected to ground for safety. In centralized inverter and string inverter systems, a high voltage gradient develops, between the PV cells and the module frame, which leads to the appearance of PID .PID particularly results in the formation of cell shunts (in the case of negatively biased PV cells), and its effect can be seen through reduced shunt resistance, as well as lower open circuit voltage and low FF. It is concluded that, in the initial stages, the degradation in performance of a PV module from PID is small at higher irradiance levels and greater under the low illumination conditions.

Defective Bypass Diodes :

Bypass diodes are installed in the PV modules in order to protect PV cells against the current mismatch result of shading and other internal defects. In installing the bypass diodes in the modules, the magnitude of breakdown voltage of a single cell is considered ; thus, a diode is generally installed for a group of about 20–24 cells. One of the main defects of the bypass diodes is the short circuit fault. A short-circuited diode can be immediately detected from the reduction in power of the PV modules. If each PV module is equipped with three bypass diodes, the underperformance is usually 1/3 of the maximum power and 1/3 of open circuit voltage . An open-circuited diode has no effect on the operation of an unshaded PV module. In the event of shading, a module with open-circuited diode can be subject to high reverse voltage. Such a PV module is highly susceptible to damage and is even a fire hazard in the case of overheating Some of the important factors for the damaging of bypass diode in PV modules are

1.When a PV module of a string is shaded (or a few cells of a single module), the bypassed diodes of the shaded module start to conduct (partial shading). Due to conduction of current, their temperature increases and can easily exceed the maximum temperature for the materials of the PV modules (≈ 85 °C). The regular operation of the bypass diodes causes spot heating in the PV modules .

2.Bypass diodes undergo thermal runaway in the event of cyclic transition from forward to reverse bias . This thermal runaway takes place when the power dissipation in the reverse biased diode is greater than the cooling capacity of the junction box.

3.Shading and fluctuations in irradiance can also lead to regular current cycling via the bypass diodes. Self-heating leads to thermal cycling.

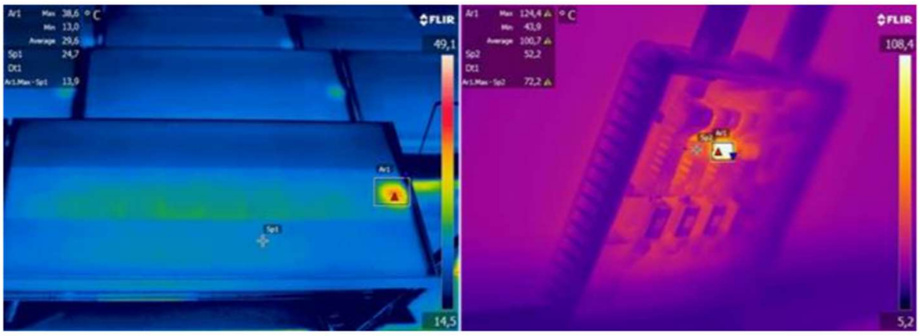


Fig 1.11 : On the left side, front view PV module with overheated junction box and on the right hand side, rear side view with open junction box and overheated diode.

Effect of Delamination :

De-lamination occurs between the two layers likely EVA and solar cell on the front surface of PV module and second between EVA and back-sheet of PV module. De-lamination occurs due to two major problems, the first one is that probability of light reflection will increase and the second is moisture will be ingress through the front surface or either back surface as shown in Fig 2.10(a). In context, sodium ion develops between glass and TCO-glass interface, its effect on the TCO and it leads to weak in less time. The result is that moisture ingress through specific part and develops the de-lamination. De-lamination also depends on the ambient temp and the material of the different additive layers such as EVA and back-sheet.

Effect of bubble

Bubble and de-lamination both depend on the detachment of the two layers, EVA-glass and EVA-back-sheet. The difference between both is that affected area of the bubble is smaller compared to the de-lamination. Bubble occurs due to overheating of solar cell and due to chemical reaction takes place than some gases are released from the backside as shown in Fig 2.10(b). In context, CO_2 (carbon dioxide), 2-ethyl hexanol and tert-butanol are involved in the formation of bubble. These gases are released during the lamination process .

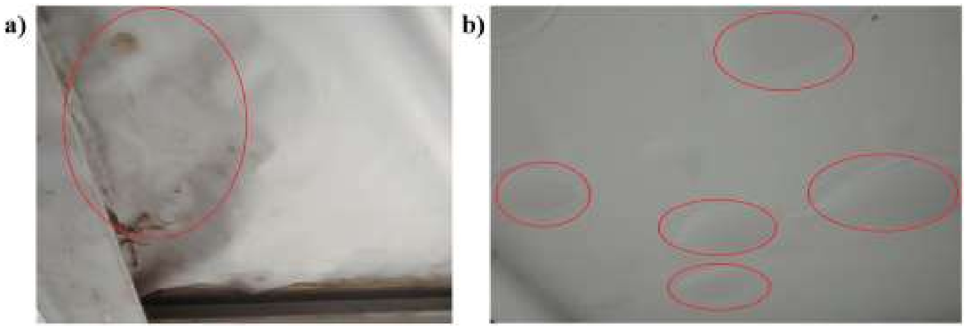


Fig 1.12 a). De-lamination in back-sheet of mono-c-Si PV module; b). Bubbles in back-sheet of mono-c-Si PV module.

1.8 Thermal Imaging:

Thermal imaging is the technique of using the heat given off by an object to produce an image of it or to locate it. This technique converts small temperature differences existing in natural scenes to a visual picture with no source of illumination required.

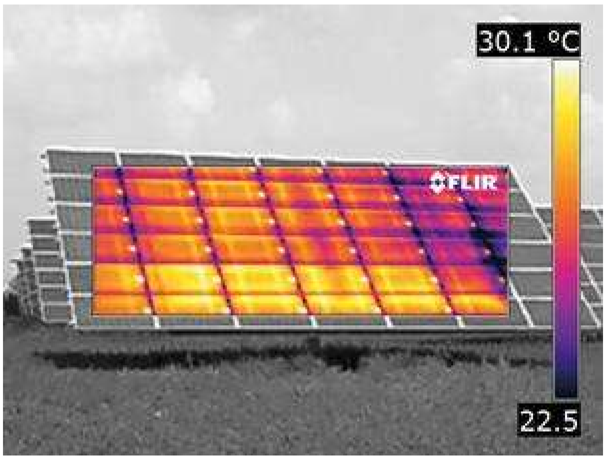


Fig 1.13 : Thermal image of a solar PV module

Thermal Image Working :

A special lens focuses the infrared light emitted by all of the objects in view. The focused light is scanned by a phased array of infrared-detector elements. The detector elements create a very detailed temperature pattern called a THERMOGRAM.

A **thermal camera** is designed to detect radiation with greater wavelengths, up to around 14,000 nm (or 14 µm).Range of thermal imager id from –5 degree centigrade to 2000 degree centigrade. Also one of the features of Thermal imaging is that it can successfully penetrate such environments as smoke, light fog, snow, rain and extreme darkness.

Advantages of thermal imaging

Non-invasive and non-destructive hence can be used while the plant is running.

Produces fast, accurate, temperature measurement and helps in fast detection of faults.

Cameras are easy to install and surveys can be performed at a convenient time.

They can be used to measure or observe subjects in areas inaccessible or hazardous for other methods.

Passively see all objects and immune to electromagnetic interference

Regular predictive maintenance using thermal imaging products help in saving money and consecutively lower the costs. This is due to less downtime, power outages, production losses, fires etc.

Some of the applications of thermal imaging are surveillance security, to find defects in solar PV modules, thermal mapping, condition monitoring, non-destructive testing, research etc

Limitations of thermal imaging

Accurate temperature measurements are hindered by differing emissivities and reflections from surfaces. Thermal imaging products require high initial investment cost. Direct thermal imaging has low spatial resolution when inspecting hot spots under bias. Thermal blurring is the main cause of such low resolution, which is caused by heat diffusion in the materials.

1.9 Electro luminescence Imaging (EL imaging):

A solar cell is an LED backwards: with a solar cell, light goes in and power comes out; with an LED, power goes in and light comes out. Electroluminescence (EL) imaging essentially converts a solar cell or module into an LED by pumping power into it. Since the bandgap of silicon, the element which constitutes >90% of solar modules, corresponds to light of a wavelength of ~1100nm, near-infrared light is emitted.

The set-up for PV EL Imaging is simple, consisting of: NIR Sensitive Camera with lens Darkened enclosure Solar Cell / Module Power Supply.

In EL images, defective cells appear darker, because disconnected parts do not irradiate. To obtain an EL image, current is applied to a PV module, which induces EL emission at a wavelength of 1,150nm. The emission can be imaged by a silicon Charge-coupled Device (CCD) sensor.

In EL images, defective cells appear darker, because disconnected parts do not irradiate.

Why take EL Images ?

An EL image is like an X-ray into a module. It allows us to see things in the module that are invisible to the naked eye. EL images are useful when trying to diagnose a problem with the module. Problems are first seen in I-V (current-voltage) curves; parameters like the current and voltage may be lower than expected, so the curve tells us that the module is underperforming. An EL image is the first step towards diagnosing why the module is underperforming by revealing what may be happening within the module. Cell cracking, interconnect breakage, cell darkening, process failures, etc., can be shown using EL images.

In general, defects in solar modules can be classified into two categories:

(1) intrinsic deficiencies due to material properties such as crystal grain boundaries and dislocations

(2) process-induced extrinsic defects such as microcracks and breaks, which reduce the overall module efficiency over time.

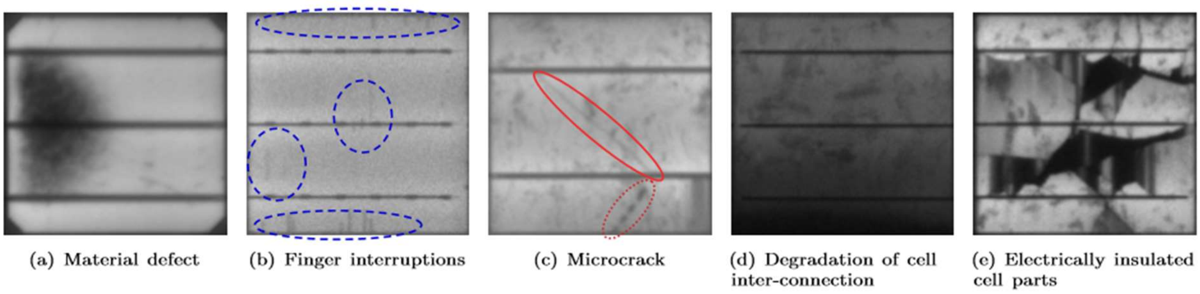


Fig 1.14: Various intrinsic and extrinsic defects in monocrystalline ((a)–(b)) and polycrystalline((c)–(e)) solar cells. (a) shows a solar cell with a typical material defect. (b) shows finger interruptions in the encircled areas, which do not necessarily reduce the module efficiency. The solar cell in (c) contains a microcrack that is very subtle in its appearance. While microcracks do

not divide the cell completely, they still must be detected because such cracks may grow over time and eventually impair the module efficiency. The spots at the bottom of this cell are likely to indicate cell damage as well. However, such spots can be oftentimes difficult to distinguish from actual material defects. (d) shows a disconnected area due to degradation of the cell interconnection. (e) shows a cell with electrically separated or degraded parts, which are usually caused by mechanical damage.

Figure 1.14 shows an example EL image with different types of defects in monocrystalline and polycrystalline solar cells. Figure 1.14(a) and Fig 1.14(b) show general material defects from the production process such as finger interruptions which do not necessarily reduce the lifespan of the affected solar panel unless caused by high strain at the solder joints. Specifically, the efficiency degradation induced by finger interruptions is a complex interaction between their size, position, and the number of interruptions. Figs 1.14(c) to 1.14(e) show microcracks, degradation of cell-interconnections, and cells with electrically separated or degraded parts that are well known to reduce the module efficiency.

Advantages of EL imaging

Electroluminescence (EL) imaging is a useful modality for the inspection of photovoltaic (PV) modules.

The high spatial image resolution enables the detection of finest defects like microcracks on the surface of PV modules and EL imaging also does not suffer from blurring due to lateral heat propagation.

It is a non-destructive technique and fairly fast with possible measurement times of 1 s.

Disadvantages of EL imaging

The analysis of EL images is typically a manual process that is expensive, time-consuming, and requires expert knowledge of many different types of defects.

1.10 Dataset Explanation:

We proposed two benchmark datasets. One dataset consists of images captured by thermal camera and another dataset consists of EL images.

Dataset-1

This dataset consists of photovoltaic systems to identify snail trails and hot spot failures. This dataset has 277 thermographic aerial images that were acquired by a Zenmuse XT IR camera (7-13 μm wavelength) from a DJI Matrice 100 drone (quadcopter). Additionally, this dataset includes the next environmental measurements: temperature, wind speed, and irradiance. The experimental set up consisted in a photovoltaic array of 4 serial monocrystalline Si panels (string) and an electronic equipment emulating a real load. The conditions for images acquisition were stablished in a flight protocol in which we defined altitude, attitude, and weather conditions.

The link for the data set is given below

https://data.mendeley.com/datasets/82vzccxb6y/2#file-4b3c5c1a-aaf8-44bd-95b3-d56672ea66fe

Number of cells	36
Dimension(mm)	1186*551*35
Weight(kg)	9
Open circuit voltage (v)	27.18
Short circuit current(A)	5.13

Table1.10.1: Solar panel specifications

Resolution(mv/mA)	1/0.1
Minimum operating voltage	0.1
Voltage range(v)	0-120

Table 1.10.2: Electronic load specifications

Dataset-2

It is a public dataset of solar cells extracted from high resolution EL images of monocrystalline and polycrystalline PV modules. The dataset consists of 2,624 solar cell images at a resolution of 300 × 300 pixels originally extracted from

44 different PV modules, where 18 modules are of monocrystalline type, and 26 are of polycrystalline type.

The solar cell dataset is available at https://github.com/zae-bayern/elpv-dataset

Total no of PV modules	44
Total no of monocrystalline modules	18
Total no of monocrystalline modules	26
Total no of solar cells	2624
No. of pixels	300*300
Total no of labelled cells used for testing	35 % (918 cells)
Total no of labelled cells used for training	65 % (1706 cells)

Table 1.10.3: Table showing the information of proposed dataset

In particular, the dataset includes microcracks and cells with electrically separated and degraded parts, short-circuited cells, open inter-connects, and soldering failures. These cell defects are widely known to negatively influence efficiency, reliability, and durability of solar modules. Finger interruptions are excluded since the power loss caused by such defects is typically negligible.

CHAPTER 2

Detection of defects using Image Processing

2.1 Introduction:

Image processing is a method to perform some operations on an image, in order to get an enhanced image or to extract some useful information from it. It is a type of signal processing in which input is an image and output may be image or characteristics/features associated with that image.

Image processing basically includes the following three steps:

- Importing the image via image acquisition tools (Image acquisition)
- Analysing and manipulating the image (Image Enhancement)
- Output in which result can be altered image or a report that is based on image analysis.

And hence various detects in the solar panels can be detected using image processing techniques. Image acquisition is the process by which the image is acquired and then the processing of the image is done by many image enhancement techniques like Histogram equivalisation, Fourier transform techniques, wiener and blind deconvolution techniques and segmentation process.

Next a classifier (SUPPORT VECTOR MACHINE) has been used to classify the defects in the solar panels and the accuracy using SVM will be determined in this chapter.

2.2 Block Diagram:

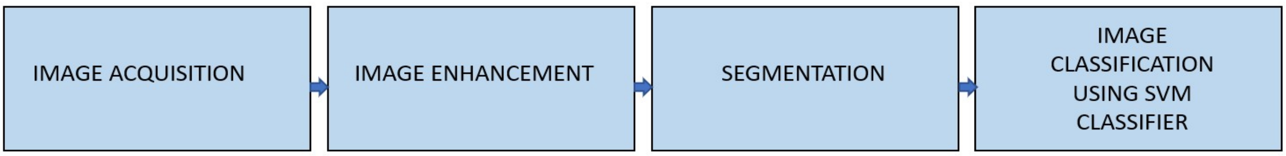


Fig 2.1 : Block diagram of the entire process occurring.

2.2.1 Image Acquisition:

To deal with images and before analysing them the most important thing is to capture the image. This is called as Image Acquisition. Image Acquisition is achieved by a suitable camera. We use different cameras for different applications.
The images of PV modules used to extract the individual solar cell samples were taken in a manufacturing setting. Such controlled conditions enable a certain degree of control on quality of imaged panels and allow to minimize negative effects on image quality, such as overexposure. Controlled conditions are also required particularly because background irradiation can

predominate EL irradiation. Given PV modules emit the only light during acquisition performed in a dark room, it can be ensured the images are uniformly illuminated. This is opposed to image acquisition in general structural health monitoring, which introduces additional degrees of freedom where images can suffer from shadows or spot lighting. An important issue in EL imaging, however, can be considered blurry (i.e., out-of-focus) EL images due to incorrectly focused lens which can be at times challenging to attain. Therefore, we ensured to include such images in the proposed dataset.

2.2.2 Image enhancement techniques:

The image has been processed using different techniques. The techniques are as follows:

1. Histogram equalisation:

Histogram is a graphical representation of the intensity distribution of an image. In simple terms, it represents the number of pixels for each intensity value considered.

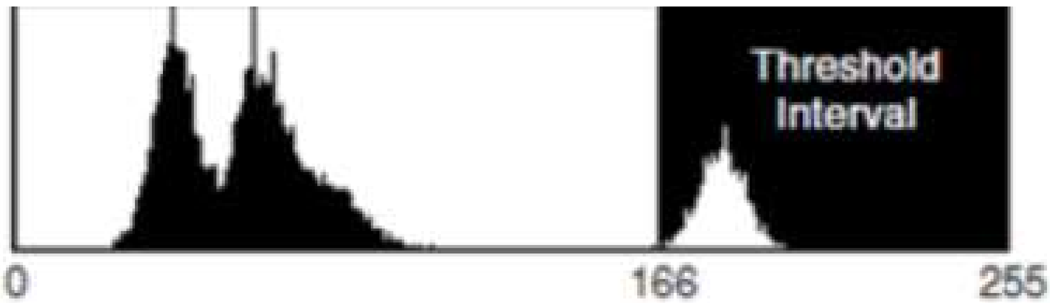


Fig 2.2(A). The threshold interval of histogram

histogram shows the number of pixels for each brightness level (from black to white) and when there are more pixels, the peak at the certain brightness level is higher.

Histogram Equalization is a computer image processing technique used to improve contrast in images. It accomplishes this by effectively spreading out the most frequent intensity values, i.e.

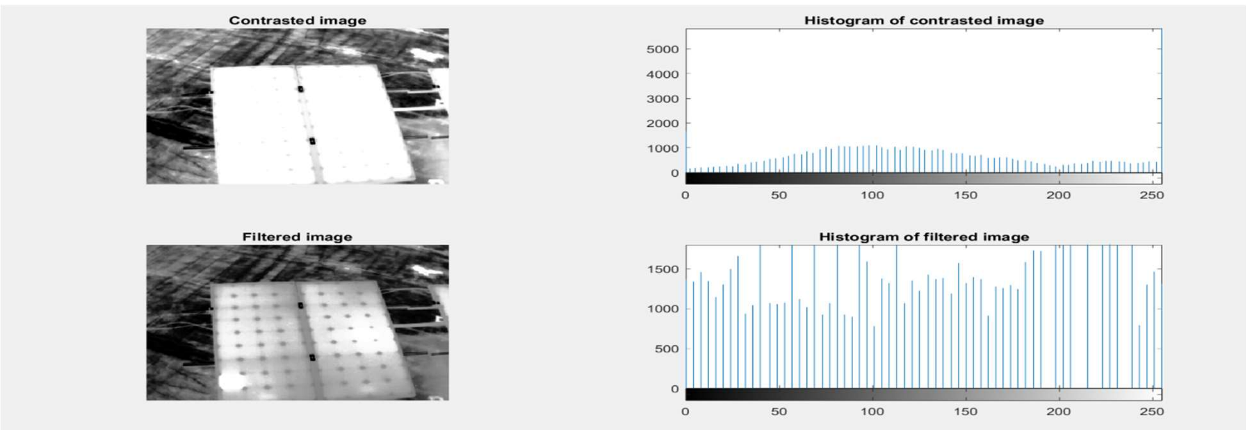


Fig 2.2(B) **:** The histograms of the contrasted and the filtered images

stretching out the intensity range of the image. This method usually increases the global contrast of images when its usable data is represented by close contrast values. This allows for areas of lower local contrast to gain a higher contrast.

2 Fourier transform techniques:

The Fourier Transform is an important image processing tool which is used to decompose an image into its sine and cosine components. The output of the transformation represents the image in the Fourier or frequency domain, while the input image is the spatial domain equivalent. In the Fourier domain image, each point represents a particular frequency contained in the spatial domain image.

The Fourier Transform is used in a wide range of applications, such as image analysis, image filtering, image reconstruction and image compression.

Because the image in the Fourier domain is decomposed into its sinusoidal components, it is easy to examine or process certain frequencies of the image, thus influencing the geometric structure in the spatial domain.

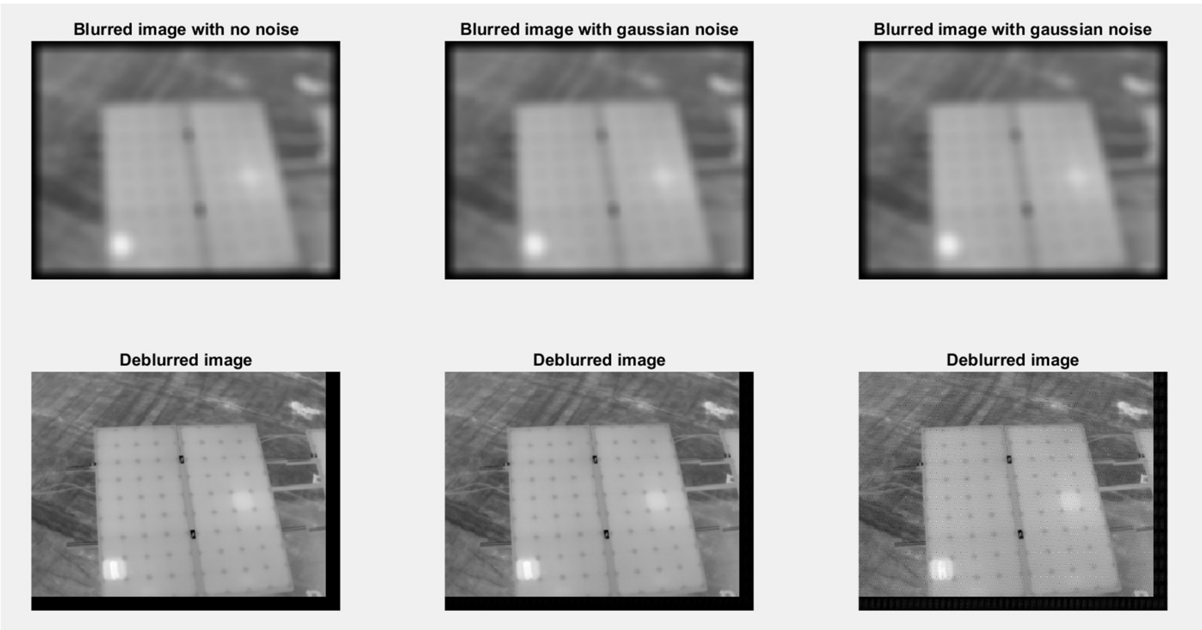


Fig 2.3 : Deblurring of the images by using Fourier transform techniques

Here in the above picture, in the first case, we have used a blurred image with no noise and have obtained the deblurred image as an output. In the next two cases, we have used a blurred image with gaussian noise and obtained the deblurred images as the output using the Fourier transform techniques.

3.Wiener and blind deconvolution :

I). Wiener deconvolution:

Wiener deconvolution is an application of the Wiener Filter to the noise problems inherent in deconvolution. It works in the frequency domain, attempting to minimize the impact of deconvolved noise at frequencies which have a poor signal to noise ratio.

The Wiener deconvolution method has widespread use in image deconvolution applications, as the frequency spectrum of most visual images is fairly well behaved and may be estimated easily.

The goal of the Wiener filter is to compute a statistical estimate of an unknown signal using a related signal as an input and filtering that known signal to produce the estimate as an output. For example, the known signal might consist of an unknown signal of interest that has been corrupted by additive noise. The Wiener filter can be used to filter out the noise from the corrupted signal to provide an estimate of the underlying signal of interest. The Wiener filter is based on a statistical approach.

The Wiener filter minimizes the mean square error between the estimated random process and the desired process. The blurred image is then processed by using this method and the output deblurred image has been obtained.

II). Blind deconvolution:

Blind deconvolution is the term given to an image restoration technique in which complete knowledge of both the point-spread function (PSF) and the object are not available.

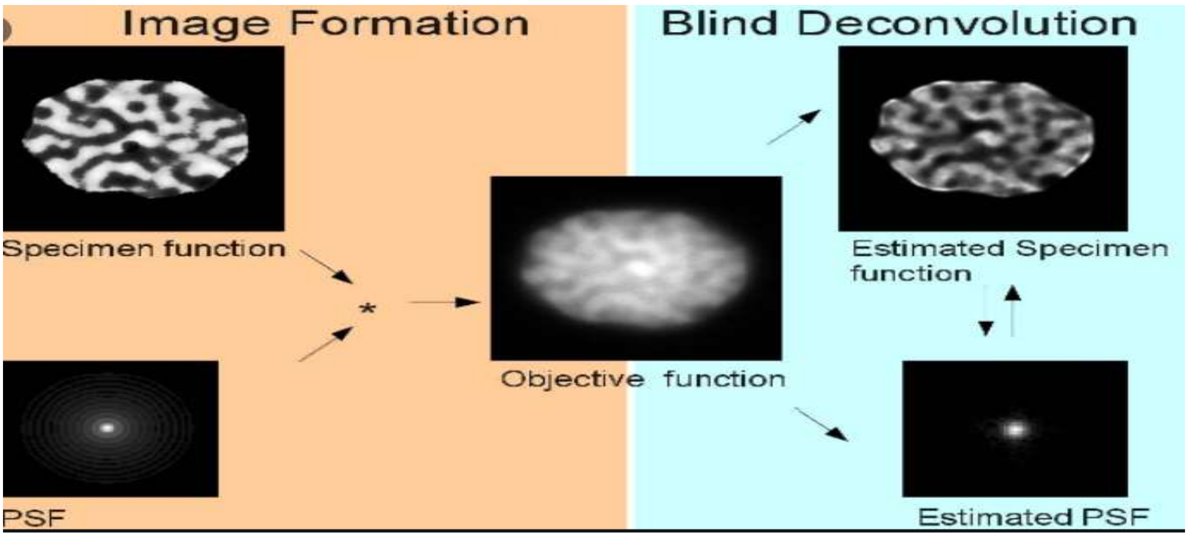


Fig 2.4 : The process of blind deconvolution

The point spread function (PSF) describes the response of an imaging system to a point source or point object. A more general term for the PSF is a system's impulse response, the PSF being the impulse response of a focused optical system

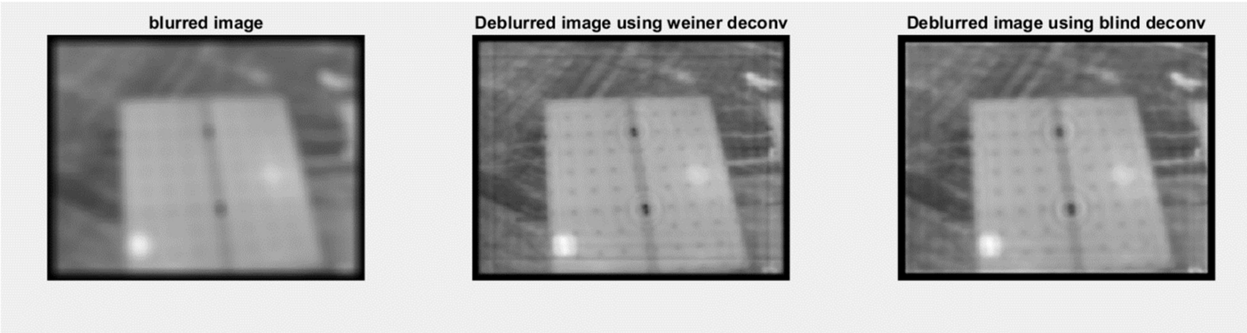


Fig 2.5 : The image enhancement of blurred image using wiener and blind deconvolution

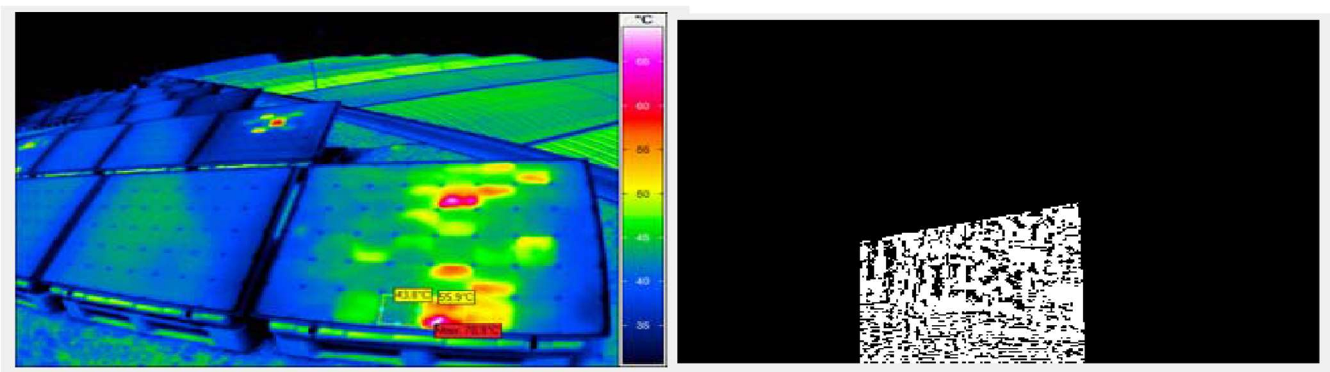
In image processing, blind deconvolution is a deconvolution technique that permits recovery of the target scene from a single or set of "blurred" images in the presence of a poorly determined or unknown point spread function (PSF). Regular linear and non-linear deconvolution techniques utilize a known PSF. For blind deconvolution, the PSF is estimated from the image or image set, allowing the deconvolution to be performed.

We have taken a blurred image and this was deblurred using wiener and blind deconvolution respectively.

2.2.3 Segmentation:

In digital image processing, **image segmentation** is the process of partitioning a digital image into multiple segments (sets of pixels, also known as image objects). The goal of segmentation is to simplify and/or change the representation of an image into something that is more meaningful and easier to analyse. Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. More precisely, image segmentation is the process of assigning a label to every pixel in an image such that pixels with the same label share certain characteristics.

The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). Each of the pixels in a region are similar with respect to some characteristic or computed property, such as colour, intensity, or texture. Adjacent regions are significantly different with respect to the same characteristics.



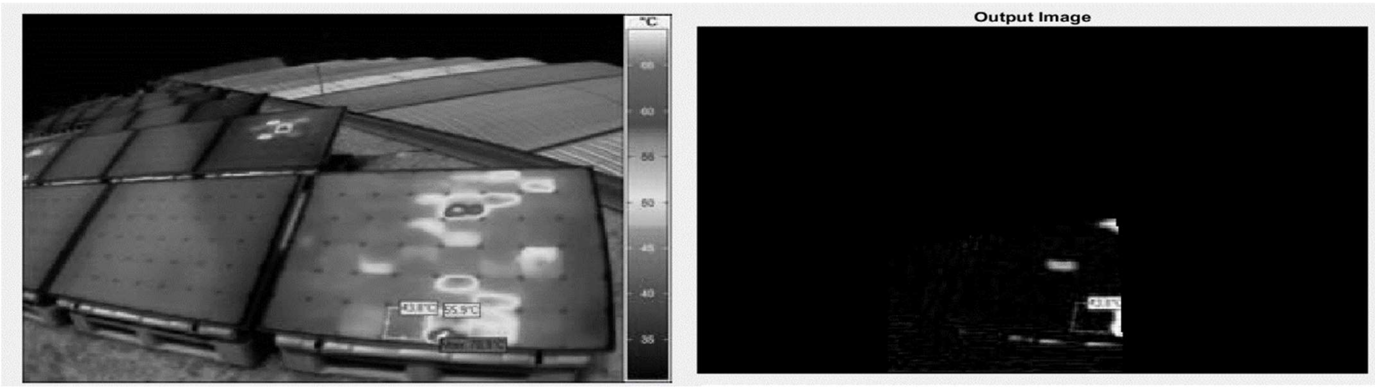


Fig 2.6(a) : The Process of segmentation

The simplest method of image segmentation is called the thresholding method. This method is based on a clip-level (or a threshold value) to turn a grey-scale image into a binary image.

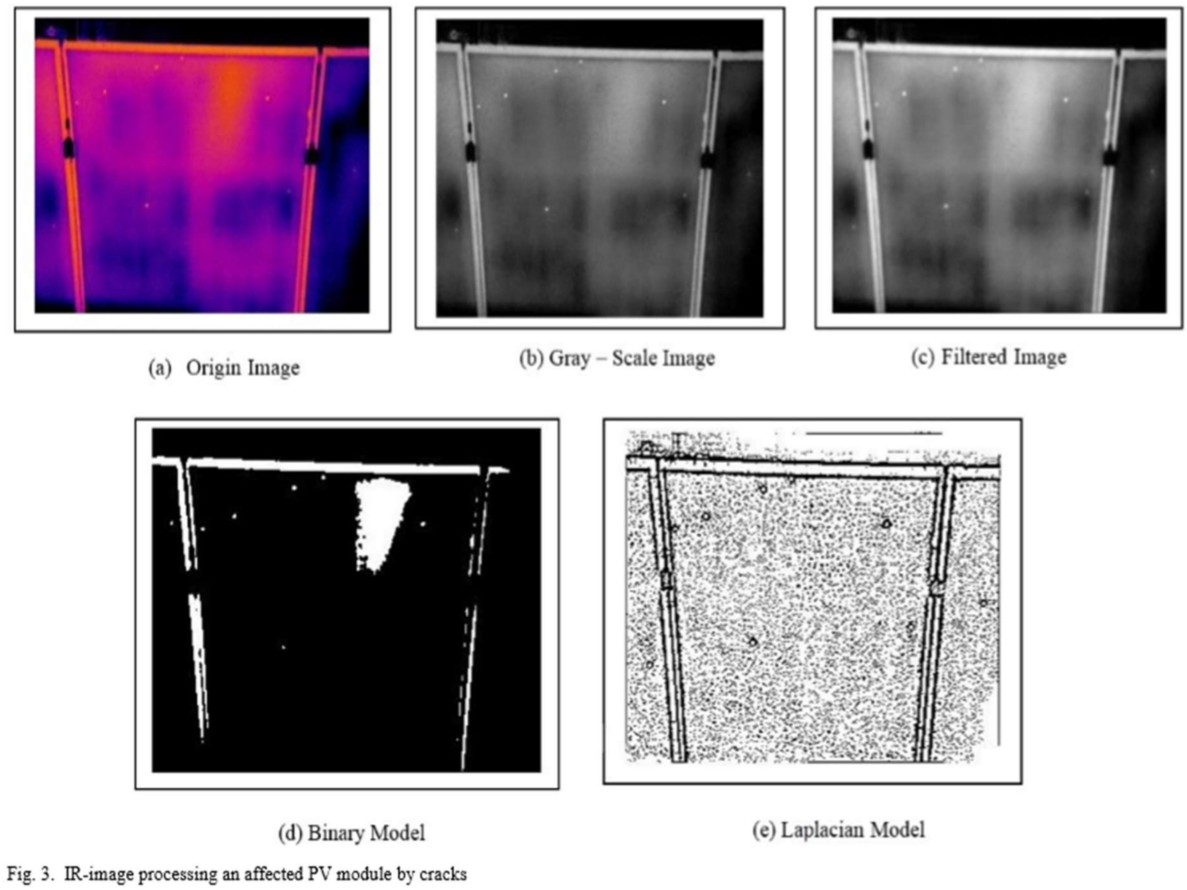


Fig 2.6 (b): The image in different models

The key of this method is to select the threshold value.

2.2.4 Image classification using SVM classifier:

What is Support Vector Machine?

Support-vector machines are supervised learning models with associated learning algorithms that analyse data used for classification and regression analysis.

The objective of the support vector machine algorithm is to find a hyperplane in an N-dimensional space (N — the number of features) that distinctly classifies the data points.

Hyperplanes are decision boundaries that help classify the data points. Data

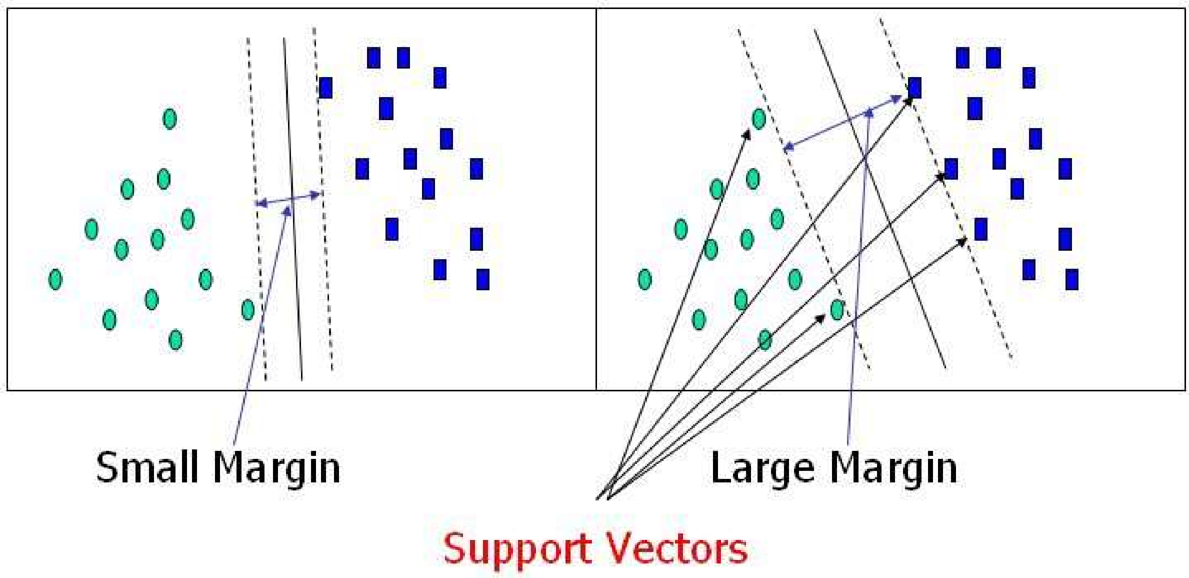


Fig 2.7 : The support vectors and the margins

points falling on either side of the hyperplane can be attributed to different classes. Also, the dimension of the hyperplane depends upon the number of features. If the number of input features is 2, then the hyperplane is just a line. If the number of input features is 3, then the hyperplane becomes a 2 -dimensional plane. It becomes difficult to imagine when the number of features exceeds 3.

Support vectors are data points that are closer to the hyperplane and influence

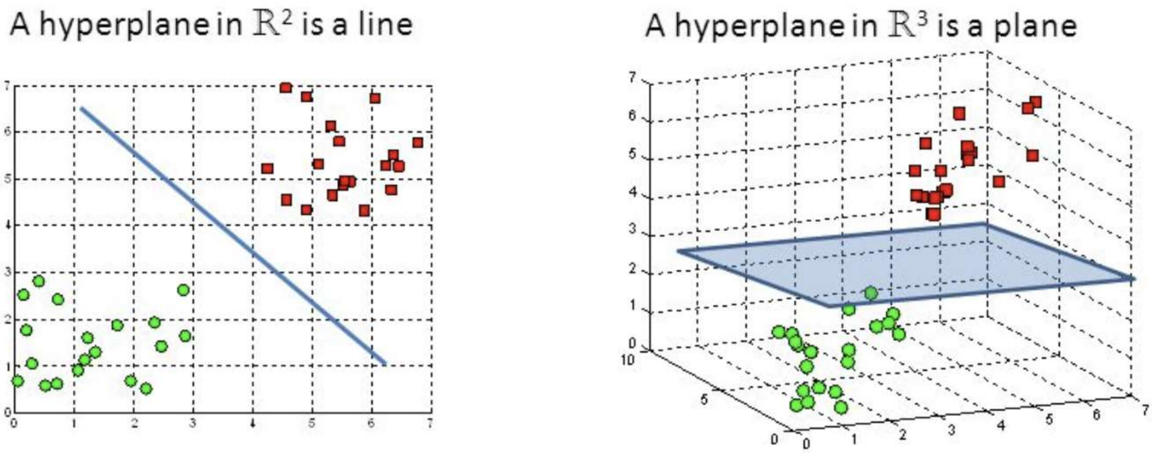


Fig 2.8 : The different forms of a hyperplane

the position and orientation of the hyperplane. Using these support vectors, we maximize the margin of the classifier. Deleting the support vectors will change the position of the hyperplane. These are the points that help us build our SVM.

Large Margin Intuition

In logistic regression, we take the output of the linear function and squash the value within the range of [0,1] using the sigmoid function. If the squashed value is greater than a threshold value(0.5) we assign it a label 1, else we assign it a label 0.

In SVM, we take the output of the linear function and if that output is greater than 1, we identify it with one class and if the output is -1, we identify is with another class.

Since the threshold values are changed to 1 and -1 in SVM, we obtain this reinforcement range of values([-1,1]) which acts as margin.

The loss function that helps maximize the margin is hinge loss.

The cost is 0 if the predicted value and the actual value are of the same sign. If they are not, we then calculate the loss value.

We also add a regularization parameter the cost function. The objective of the regularization parameter is to balance the margin maximization and loss.

After adding the regularization parameter, the cost functions looks as below.

$$min_w \lambda \parallel w \parallel^2 + \sum_{i=1}^{n} (1 - y_i \langle x_i, w \rangle)_+$$

Loss function for SVM

Now that we have the loss function, we take partial derivatives with respect to the weights to find the gradients. Using the gradients, we can update our weights by the adjacent formula.

$$\frac{\delta}{\delta w_k} \lambda \parallel w \parallel^2 \; = 2\lambda w_k$$

$$\frac{\delta}{\delta w_k} \big(1 - y_i \langle x_i, w \rangle\big)_+ \; = \begin{cases} 0, & \text{if } y_i \langle x_i, w \rangle \geq 1 \\ -y_i x_{ik}, & \text{else} \end{cases}$$

Gradients

When there is no misclassification, that is our model correctly predicts the class of our data point, we only have to update the gradient from the regularization parameter.

$$w = w - \alpha \cdot (2\lambda w)$$

Gradient Update — No misclassification

When there is a misclassification, that is our model make a mistake on the prediction of the class of our data point, we include the loss along with the regularization parameter to perform gradient update.

$$w = w + \alpha \cdot (y_i \cdot x_i - 2\lambda w)$$

Gradient Update — Misclassification

A Kernel function transforms the training data so that a non-linear decision surface is transformed to a linear equation in a higher number of dimensions. Linear discriminant functions can provide very efficient 2-class classifiers, provided that the class features can be separated by a linear decision surface. For many domains, it is easier to separate the classes with a linear function if you can transform your feature data into a space with a higher number of dimensions. One way to do this is to transform the features with a "kernel" function.

2.3 SVM Implementation in Python:

The dataset that we have taken is from the link: https://github.com/zae-bayern/elpv-dataset

The code has been written in python and image has been used as a feature and type as a label. The probability has been totally disregarded. The code is provided in the appendix below.

2.4 Result and Conclusion:

The no. of cells used here in the code are 300x300 cells with 8 -bit grayscale. The overall accuracy obtained in the code for Support vector machine is 99.74%.

Hence, we are successfully able to detect likelihood of a defect using a Support vector machine model. The accuracy obtained is quite high. SVM algorithm is not suitable for large data sets. SVM is quite an exciting algorithm and the concepts related to it are quite simple.

The various limitations of Support vector machine are:

SVM does not perform very well, when the data set has more noise (i.e. target classes are overlapping). In cases where number of features for each data point exceeds the number of training data sample, the SVM will underperform. Hence, we will further be using the model of Convolutional neural networks (CNN) to detect the accuracy and to classify the defects.

CHAPTER 3

Detection of defects using Neural Networks

3.1 Neural Networks:

Neural networks are a set of algorithms, modelled loosely after the human brain, that are designed to recognize patterns. The patterns they recognize are numerical, contained in vectors, into which all real-world data, be it images, sound, text or time series, must be translated. They help to group un labelled data according to similarities among the example inputs, and they classify data when they have a labelled dataset to train on.

All classification tasks depend upon labelled datasets; that is, humans must transfer their knowledge to the dataset in order for a neural network to learn the correlation between labels and data. This is known as supervised learning.

- Detect faces, identify people in images, recognize facial expressions (angry, joyful)
- Identify objects in images (stop signs, pedestrians, lane markers…)
- Recognize gestures in video
- Detect voices, identify speakers, transcribe speech to text, recognize sentiment in voices
- Classify text as spam (in emails), or fraudulent (in insurance claims); recognize sentiment in text (customer feedback)

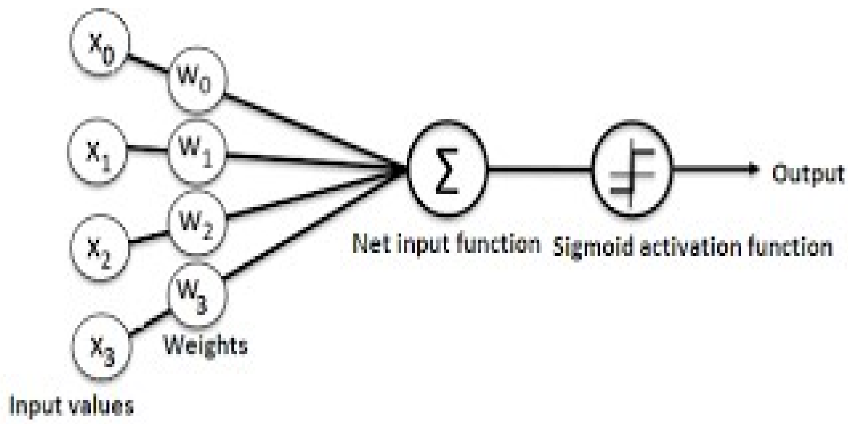


Fig 3.1 : A Simple Neural Network

Any labels that humans can generate, any outcomes that you care about and which correlate to data, can be used to train a neural network.

Learning without labels is called unsupervised learning.

Unlabelled data is the majority of data in the world. One law of machine learning is: the more data an algorithm can train on, the more accurate it will be. Therefore, unsupervised learning has the potential to produce highly accurate models.

- Search: Comparing documents, images or sounds to surface similar items.
- Anomaly detection: The flipside of detecting similarities is detecting anomalies, or unusual behaviour. In many cases, unusual behaviour correlates highly with things you want to detect and prevent, such as fraud.

3.2 Different Types of Neural Networks:

Three important types of neural networks that form the basis for most pre- trained models in deep learning are:

- Artificial Neural Networks (ANN)
- Convolution Neural Networks (CNN)
- Recurrent Neural Networks (RNN)

Artificial Neural Network (ANN)

Artificial Neural Network, or ANN, is a group of multiple perceptrons/ neurons at each layer. ANN is also known as a **Feed-Forward Neural network** because inputs are processed only in the forward direction.

ANN consists of 3 layers – Input, Hidden and Output.

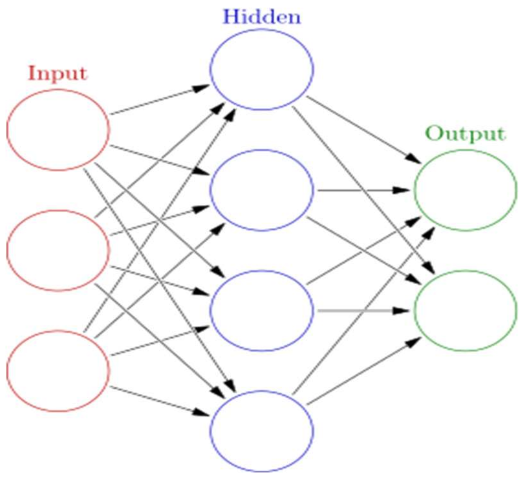


Fig 3.2: Artificial neural network

The input layer accepts the inputs, the hidden layer processes the inputs, and the output layer produces the result. Essentially, each layer tries to learn certain weights.

ANN can be used to solve problems related to tabular data ,Image data, Text data.

Advantages of Artificial Neural Network (ANN)

Artificial Neural Network is capable of learning any nonlinear function. Hence, these networks are popularly known as Universal Function Approximators.

ANNs have the capacity to learn weights that map any input to the output.

One of the main reasons behind universal approximation is the **activation function**. Activation functions introduce nonlinear properties to the network. This helps the network learn any complex relationship between input and output. the output at each neuron is the activation of a weighted sum of inputs. The network only learns the linear function and can never learn complex relationships if there is no activation function

Challenges with Artificial Neural Network (ANN)

ANN cannot capture sequential information in the input data which is required for dealing with sequence data

Recurrent Neural Network (RNN)

Recurrent neural networks to solve the problems related to time Series data, text data audio data

RNN has a recurrent connection on the hidden state.

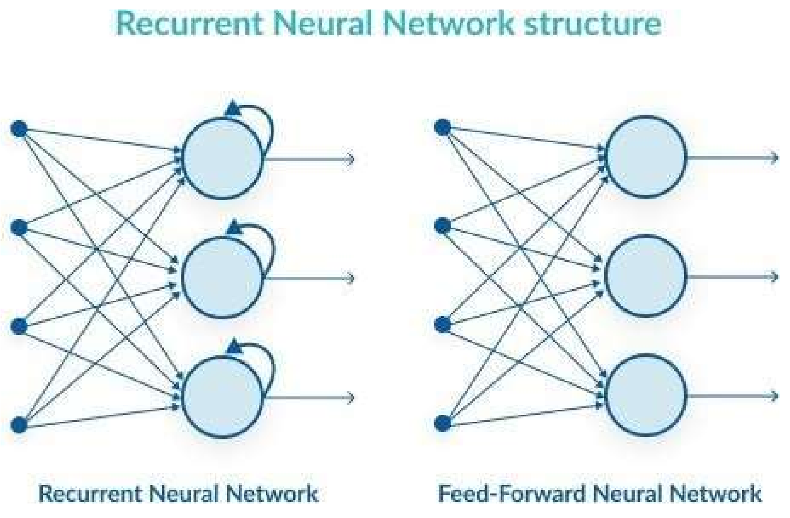


Fig 3.3 : Figure showing recurrent neural network and feed-forward neural network

This looping constraint ensures that sequential information is captured in the input data.

Advantages of Recurrent Neural Network (RNN)

RNN captures the sequential information present in the input data i.e. dependency between the words in the text while making predictions

Convolution Neural Network (CNN)

The building blocks of CNNs are filters a.k.a. kernels. Kernels are used to extract the relevant features from the input using the convolution operation.

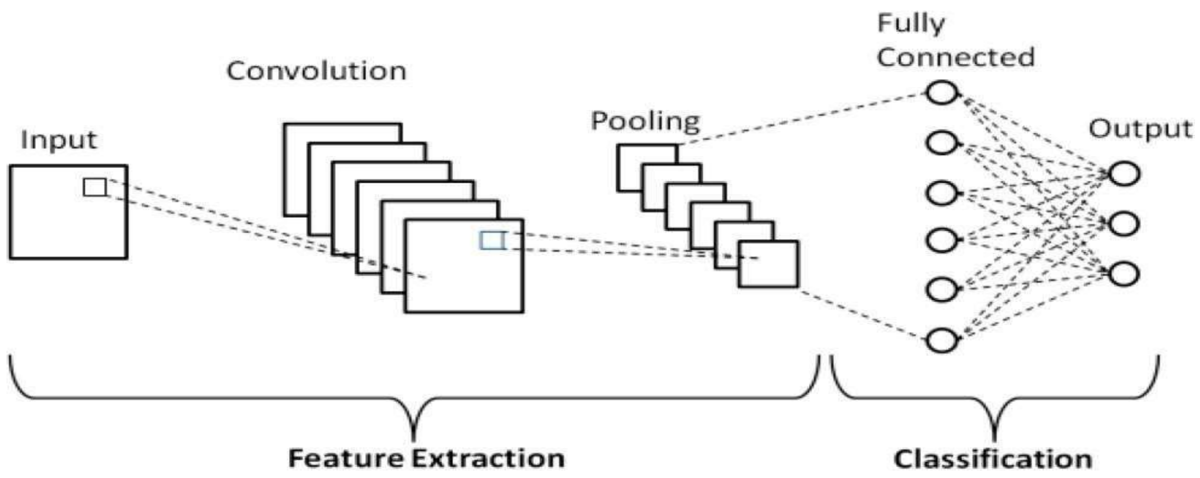


Fig 3.4: A convolution neural network showing different layers

Mainly used for image and video processing projects. convolutional neural networks were introduced to solve problems related to image data; they perform impressively on sequential inputs as well.

Advantages of Convolution Neural Network (CNN)

CNN learns the filters automatically without mentioning it explicitly. These filters help in extracting the right and relevant features from the input data CNN captures the **spatial features** from an image. Spatial features refer to the arrangement of pixels and the relationship between them in an image. They help us in identifying the object accurately, the location of an object, as well as its relation with other objects in an image

CNN also follows the concept of parameter sharing. A single filter is applied across different parts of an input to produce a feature map

One common problem in all these neural networks is the Vanishing and Exploding Gradien**t**. This problem is associated with the backpropagation algorithm. The weights of a neural network are updated through this backpropagation algorithm by finding the gradients

Comparing the Different Types of Neural Networks (MLP(ANN) vs. RNN vs. CNN)

	MLP	RNN	CNN
Data	Tabular data	Sequence data (Time Series,Text, Audio)	Image data
Recurrent connections	No	Yes	No
Parameter sharing	No	Yes	Yes
Spatial relationship	No	No	Yes
Vanishing & Exploding Gradient	Yes	Yes	Yes

Table 3.1 : Table comparing different types of neural networks

3.3 Convolutional Neural Network:

The name "convolutional neural network" indicates that the network employs a mathematical operation called Convolution. Convolution is a specialized kind of linear operation. Convolutional networks are simply neural networks that use convolution in place of general matrix multiplication in at least one of their layers.

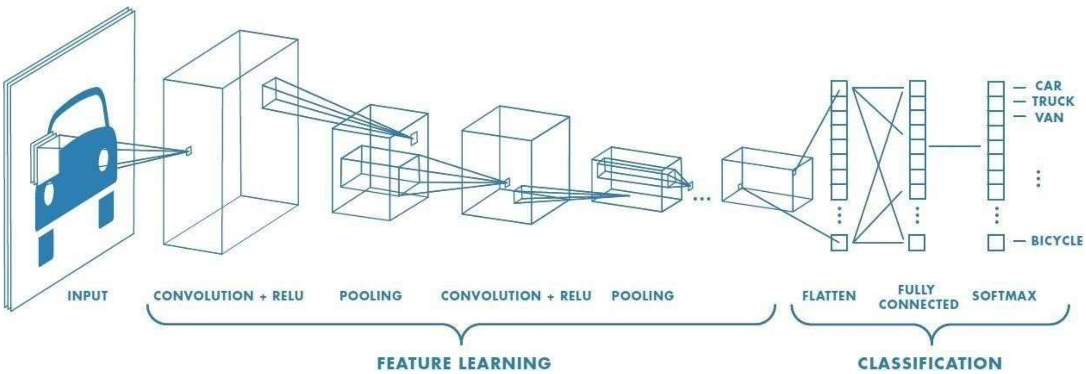


Fig 3.5 : Convolution neural network showing feature learning and classification and different layers involved

First of all , , input images are processed in the background using pixel information that lies in an image.

For a black and white image pixel information will be 0 or 1 it means if in a cell if 0 is there then it is white, if 1 is there then it is black.

For a colored image generally each pixel information composes of 3 combined (red + green + blue) information.

Since red, green, blue all three when combined you get all kinds of colors, for pixel data you need to combine data of all three which are red, green, blue.

3.3.1 Convolution Layer:

In convolution there is a key concept which is very much useful which is called feature detector.

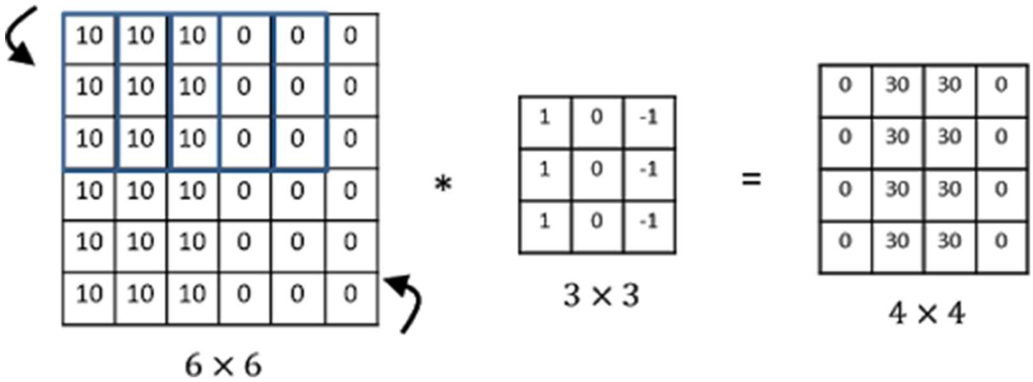


Fig 3.6 :Input Image feature detector feature map

A feature detector is a matrix which has values corresponding to a particular feature. This has data which is useful to capture specific features that lie inside an image. There can be lots of feature detectors in a CNN. When you use this feature detector on an input image you get a feature map.

Feature detector can detect features like the color of the image, it can also detect the presence of an eye in an image. As we go deep into the layers, we get more deeper features. Let's say for example we have to classify vehicles, then, on first layer of convolution we get features like the color of vehicle, no.of wheels it has etc. But as we go into deeper layers feature detectors detect more deeper features.

Thus, after each convolution layer you get a layer of convolutional layer which comprises of lots of feature maps corresponding to feature detectors.

Sometimes convolution calculations can be time taking.

3.3.2 Pooling:

This convolution layer is passed through pooling

There are many types of pooling like max pooling, average pooling

Max Pooling :

Max pooling is useful to capture only important parts of an image. In this method depending on the output size after pooling you only take maximum values. This is useful to shorten the size which improves efficiency of CNN. It also eliminates unnecessary content in the image.

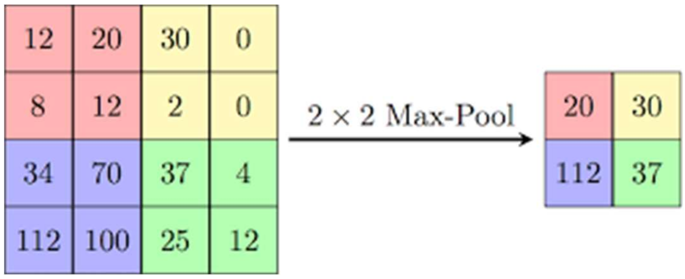


Fig 3.7 : Max Pooling Matrix

Average pooling:

Average pooling is useful to capture useful parts of an image on an average. In this method depending on the output size after pooling you take average of values. This is useful to shorten the size which improves efficiency of CNN.

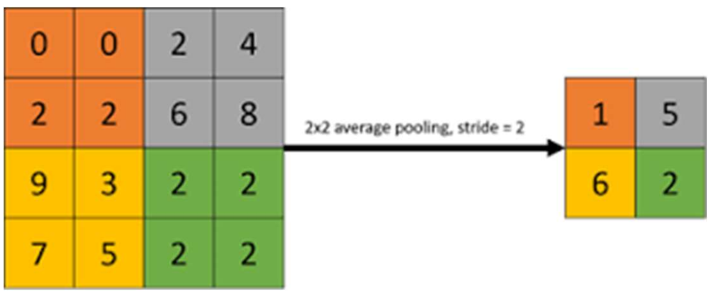


Fig 3.8 : Average Pooling Matrix

Average pooling and Max pooling both are used depending on the application that model performs. It is known that for many applications max pooling is used as default.

After pooling is done, we get a pooling layer.

These Convolution and Pooling both are applied many times for accuracy and efficiency.

After this is done Flattening is performed

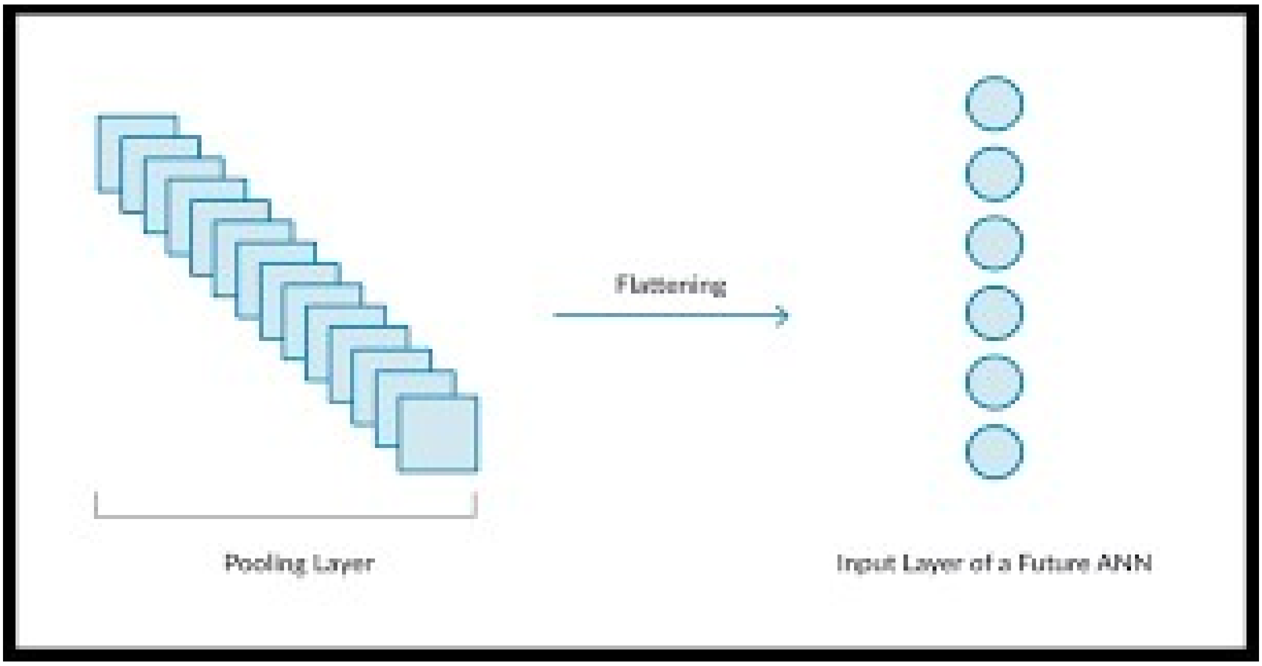


Fig 3.9 : Transformation from Pooling to Flattening Layer

The reason we do flattening is that later we are going to need to insert data into an ANN later.

The obtained layer after flattening is passed through a fully connected ANN.

3.3.3 SoftMax Function:

SoftMax activation function is used finally for classification since it is proven to be more accurate with results.

The following image shows formula for SoftMax function. It makes any value in between 0 and 1.

$$\boxed{\sigma(x_j) = \frac{e^{x_j}}{\sum_i e^{x_i}}}$$

3.4 CNN Implementation in Python:

The dataset that we have taken is from the link: https://github.com/zae-bayern/elpv-dataset

The code has been written in python and image has been used as a feature and type as a label. The probability has been totally disregarded.

The link for the code is: https://github.com/satyasaiteja/Project

3.5 Result:

We have used 35% of cells for training and 65% cells for testing. We have obtained the following results which are tabulated

Type	Mono-crystalline	Poly-crystalline
Functional	95%	95.4%
Defective	95.2%	95.5%

Table 3.2: Quantitative results using CNN model

3.6 Conclusion:

Hence, we are successfully able to detect functional and defective modules of mono-crystalline and poly-crystalline PV modules using a convolution neural network. The high accuracies make CNN classifiers useful for visual inspection. If the application scenario permits the usage of GPUs and higher processing times, the computationally more expensive CNN is preferred.

Accuracy:

On an average accuracy of **95.3%** is obtained using convolution neural network. Accuracy can be increased by providing more training data.

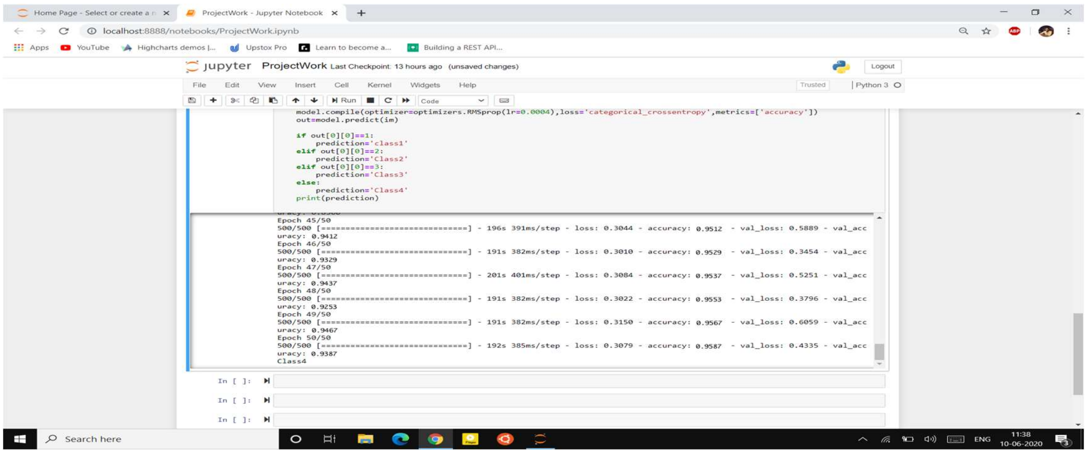


Fig 3.10: Image showing simulation result

We have provided the training data into 4 classes. They are as follows

1.Defective mono-crystalline

2. Defective poly-crystalline

3. functional poly-crystalline

4. Functional mono-crystalline

In the image it is showing as class 4 which is a functional mono-crystalline PV module and accuracy as 95%.

3.7 Comparision of SVM and CNN:

In this work, we investigated two approaches for automatic detection of defects in a single image of a PV cell. The approaches differ in their hardware requirements, which are dictated by their respective application scenarios. The more hardware-efficient approach is based on hand-crafted features that are classified in a Support Vector Machine (SVM). The more hardware-demanding approach is an end-to-end deep Convolutional Neural Network (CNN) that runs on a Graphics Processing Unit (GPU). Both approaches are trained on 1,968 cells extracted from high resolution EL intensity images of mono- and polycrystalline PV modules. The CNN is more accurate, and reaches an average accuracy of 95.3%. The SVM achieves a slightly higher average accuracy of 99%, but can run on arbitrary hardware. Both automated approaches make continuous, highly accurate monitoring of PV cells feasible. If the application scenario permits the usage of GPUs and higher processing times, the computationally more expensive CNN is preferred. Otherwise, the SVM classifier is a viable alternative for applications that require a low resource footprint.

3.7 Future Work:

Instead of predicting the defect likelihood one may want to predict specific defect types. Given additional training data, the methodology presented in this work can be applied without major changes (e.g., by fine-tuning to the new defect categories) given additional training data with appropriate labels. Fine-tuning the network to multiple defect categories with the goal of predicting defect types instead of their probabilities, however, will generally affect the choice of the loss function and consequently the number of neurons in the last activation layer. A common choice for the loss function for such tasks is the (categorical) cross entropy loss with SoftMax activation.

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APPENDIX

1. The SVM code (written in python) is as follows:

```
import os
import pandas as pd
import numpy as np
from PIL import Image
from sklearn import svm
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder ,LabelEncoder
from sklearn import metrics



#just change path to run

# example path

# path = r'C:\Users\renuka\Desktop\elpv-dataset-master'

Path = r’’

os.chdir(path)

def load_dataset(fname=None):

if fname is None:

# Assume we are in the utils folder and get the absolute path to the

# parent directory.

fname = os.path.abspath(os.path.join(os.path.dirname(__file__),
os.path.pardir))

fname = os.path.join(fname, 'labels.csv')

data = np.genfromtxt(fname, dtype=['|S19', '<f8', '|S4'], names =[ 'path', 'probability',
'type'])
image_fnames = np.char.decode(data['path'])
probs = data['probability']
types = np.char.decode(data['type'])
def load_cell_image(fname):
```

```
 with Image.open(fname) as image:
 return np.asarray(image)
dir = os.path.dirname(fname)
images = np.array([load_cell_image(os.path.join(dir, fn))  for fn in image_fnames])
return images, probs, types
In [14]: temp = load_dataset('labels.csv')
In [15]: temp Out[15]:
(array([[[14, 14, 14, ...,  9,  9,  9],
[15, 15, 15, ..., 10,  9,  9],
[15, 15, 16, ..., 10, 10, 10],         ...,
[29, 29, 29, ..., 19, 18,  4],
[29, 29, 29, ..., 18, 18,  4],
[29, 29, 29, ..., 18, 18,  4]],


[[29, 29, 29, ..., 17, 16,  3],

[29, 29, 29, ..., 17, 16,  3],

[29, 29, 29, ..., 16, 15,  3],         ...,

[21, 22, 21, ..., 12, 12, 11],

[20, 20, 20, ..., 12, 12, 11],

[19, 19, 18, ..., 12, 12, 10]],

[[29, 29, 30, ..., 19, 18,  4],

[29, 30, 30, ..., 19, 18,  4],

[30, 30, 31, ..., 18, 18,  3],         ...,

[35, 35, 35, ..., 21, 12,  0],

[35, 35, 35, ..., 21, 12,  0],

[35, 35, 35, ..., 21, 12,  0]],


       ...,

[[66, 65, 62, ..., 62, 62, 62],
[64, 62, 61, ..., 60, 60, 61],
[63, 61, 59, ..., 61, 60, 60],         ...,
```

```
[45, 50, 55, ..., 57, 51, 47],
[45, 47, 48, ..., 52, 49, 46],
[43, 43, 44, ..., 48, 46, 44]],

 [[64, 65, 64, ..., 68, 69, 67],
[62, 62, 63, ..., 66, 67, 66],
[61, 60, 61, ..., 68, 67, 67],        ...,
[47, 45, 46, ..., 54, 48, 48],
[44, 42, 42, ..., 53, 47, 47],
[44, 41, 41, ..., 51, 46, 46]],

 [[67, 68, 66, ..., 64, 64, 63],
[67, 67, 66, ..., 63, 62, 63],
[67, 66, 64, ..., 66, 63, 63],        ...,
[48, 48, 49, ..., 65, 55, 50],
[46, 45, 45, ..., 59, 51, 47],
[44, 43, 42, ..., 51, 47, 45]]],
dtype=uint8),
array([1., 1., 1., ..., 0., 0., 0.]),
array(['mono', 'mono', 'mono', ..., 'poly', 'poly', 'poly'], dtype ='<U4'))
In [16]:
images = temp[0]
prob = temp[1]
panel_type = temp[2]
X = []
y = []
for i in range(len(images)):
X.append(images[i].flatten() )
y.append(panel_type[i])
In [24]: le = LabelEncoder()
y = le.fit_transform(y)
Out[24]: array([0, 0, 0, ..., 1, 1, 1], dtype=int64)

In [27]: X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,random_s
tate=109)
In [37]: clf = svm.SVC(kernel='rbf')
clf.fit(X_train, y_train)
Out[37]: SVC(C=1.0, break_ties=False, cache_size=200, class_weight=None, coef
0=0.0,    decision_function_shape='ovr', degree=3, gamma='scale', kernel ='rbf',
```

max_iter=-1, probability=False, random_state=None, shrinking=Tru e, tol=0.001, verbose=False)

In [38]: y_pred = clf.predict(X_test)
In [39]: print("Accuracy:",metrics.accuracy_score(y_test, y_pred))
Accuracy: 0.9974619289340102

In [40]: print("Precision:",metrics.precision_score(y_test, y_pred))
Precision: 0.9955849889624724
print("Recall:",metrics.recall_score(y_test, y_pred))

2. The CNN Implementation Code as Follows :

```
from keras.layers import Dense,Flatten,Dropout
from keras.models import Sequential
from keras.layers import Convolution2D,MaxPooling2D
import cv2,numpy as np
from keras.models import load_model
import glob
from keras import optimizers
#training set images should be separated as folders of their corres output
def create_cnn(model_path=None):
#initialization
classifier=Sequential()
#Convolution
classifier.add(Convolution2D(32,3,3,input_shape=(64,64,3),activation='relu'))
#Pooling
classifier.add(MaxPooling2D(pool_size=(2,2)))
#Dropout
classifier.add(Dropout(0.5))
#Adding 2nd conv. layaer
```

```
classifier.add(Convolution2D(32,3,3,activation='relu'))
classifier.add(MaxPooling2D(pool_size=(2,2)))
classifier.add(Dropout(0.5))
classifier.add(Convolution2D(64,3,3,activation='relu'))
classifier.add(MaxPooling2D(pool_size=(2,2)))
classifier.add(Dropout(0.5))
#Flattening
classifier.add(Flatten())
#Full Connected Layers
classifier.add(Dense(output_dim=128,activation='relu'))
classifier.add(Dropout(0.5))
classifier.add(Dense(output_dim=128,activation='relu'))
classifier.add(Dropout(0.5))
classifier.add(Dense(output_dim=4,activation='softmax'))
#compliling CNN important to remem loss fun and optimizer
classifier.compile(optimizer=optimizers.RMSprop(lr=0.0004),loss='categorical_crossentro
py',metrics=['accuracy'])
#Fitting CNN to Images
from keras.preprocessing.image import ImageDataGenerator
train_datagen = ImageDataGenerator(
rescale=1./255,
shear_range=0.2,
zoom_range=0.2,
horizontal_flip=True)
test_datagen = ImageDataGenerator(rescale=1./255)
training_set = train_datagen.flow_from_directory(
'C:\\Users\\Satya Karuturi\\Documents\\GitHub\\elpv-dataset\\images',
target_size=(64, 64),
batch_size=32,
class_mode='categorical')
test_set = test_datagen.flow_from_directory(
'C:\\Users\\Satya Karuturi\\Documents\\GitHub\\elpv-dataset\\images',
target_size=(64,64),
batch_size=32,
class_mode='categorical')
classifier.fit_generator(
training_set,
steps_per_epoch=8000,
epochs=35,
validation_data=test_set,
validation_steps=2000)
#saving the model with this name
classifier.save('classifier.h5')
```

```
if model_path:
model=load_model('classifier.h5')
return model
if __name__ == "__main__":
#Opening the image for prediction
file_path='C:\\Users\\Satya Karuturi\\Documents\\GitHub\\elpv-
dataset\\Im2\\cell0001.png',
im=cv2.resize(cv2.imread(file_path),(64,64)).astype(np.float32)
#cv2.imshow('Sample',cv2.resize(cv2.imread(file_path),(640,480)))
im = np.expand_dims(im, axis=0)
#Checking if model is present in the Directory
if(glob.glob('*.h5')):
for filename in glob.glob('*.h5'):
model=load_model(filename)
print('Model Loaded')
else:
print('Model Not found, Creating a new M')
model=create_cnn('classifier.h5')
#Compiling the model and predicting Output
model.compile(optimizer=optimizers.RMSprop(lr=0.0004),loss='categorical_crossentropy'
,metrics=['accuracy'])
out=model.predict(im)
if out[0][0]==1:
prediction='class1'
elif out[0][0]==2:
prediction='Class2'
elif out[0][0]==3:
prediction='Class3'
else:
prediction=='Class4'
print(prediction)
```